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PREDICTING EFFECTS OF CLIMATE FLUCTUATIONS FOR WATER MANAGEMENT BY APPLYING NEURAL NETWORKS

Eric Zhang and Paul Trimble
Hydrologic Systems Modeling Division
Planning Department
South Florida Water Management District
West Palm Beach, Florida 33406 USA

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SUMMARY

The ability to forecast hydrologic effect of climate fluctuations would be a valuable asset to regional water management authorities such as the South Florida Water Management District, These forecasts may provide advanced warnings of possible extended periods of deficits or surpluses of water availability' allowing better regional water management for flood protection, water supply, and environmental enhancement, In order to achieve this goal, it is necessary to have a global perspective of the oceanic and atmospheric phenomena which may affect regional water resources, however, the complexity involved may hinder traditional analytical approaches in forecasting because such approaches are based on many simplified assumptions about the natural phenomena.

This paper investigates the applicability of neural networks in climate based forecasting for regional water resources management. A neural network is a computational method inspired by studies of the brain and nerve systems in biological organisms. Neural networks represent highly' idealized mathematical models of our present understanding of such complex systems. Typically, a neural network consists of a set of layered processing units and weighted interconnections between the units. There exists a variety of neural network models and learning procedures. This paper applies the most widely used Back Propagation model to the climate forecasting. An advantage of applying this technique is that neural networks have the capability of self-learning, and automatic abstracting. The users do not have to know, and in many' cases they do not know, the mathematical expressions of the variables involved. Neural networks learn from training data sets.

While the architecture of the Back Propagation network is fairly established, the process of determining the best suitable network configuration and the best parameters for a given application is trial-and-error, especially when the relationships between the variables are not well understood. On the other hand, this trial-and-error process can be

used to help reveal the underlining relationships between variables. In this study, issues such as selecting a best fit neural network configuration, deploying a proper training algorithm, and preprocessing input data are addressed. The effects of various global oceanic and atmospheric variables to the regional water resources are also discussed.

The study is focused on the prediction of inflow to Lake Okeechobee, the liquid heart for south Florida. Several global weather parameters over the past several decades are used as input data for training and testing. Different combinations of the variables are explored. Our preliminary results show that the neural networks are promising tools in this type of forecasting.

INTRODUCTION

Regions of south and central Florida have experienced a significant large-scale downward trend in it's wet season (May-October) rainfall in recent decades(Chin 1993). The rainfall during these months is critical for replenishing the system storage prior to the dry season which follows (November-April). The last few years since 1990 have offered a break in the decline in rainfall. However, the question arises whether this is a reversal of a trend or just a temporary reprieve. Rasmusson and Arkin (1993) did a nice job in making it clear that a global understanding of climate is needed to understand the reason and causes of local anomalies. They also summarize inter-decadal fluctuation in climate in the Sahel and India that appear to have very similar climate trends as those in South Florida. A better understanding of how local climate fluctuations in Florida are related to global climate shifts over time would be a useful tool for managing water levels of the present regional hydrologic system and for planning future water supply plans for this system. In addition, the predictability of trends in Florida's local meteorological variables caused by global climate fluctuations would undoubtedly be an important step, however small, to a better understanding of what effect global warming may have on our local climate.

The purpose of this research is to: l) gain a better understanding of how climate fluctuations within the south and central Florida region may be related to global climate fluctuations or trees; 2) determine if decadal fluctuations in the local climate may be explained by global climate indices; and, 3) to determine, if such a relationship exists, can it be applied for more effectively managing the water levels and outflows of Lake Okeechobee. A neural network is used to test the predictability of Lake Okeechobee tributary inflows from global climate indices. The indices associated with Pacific Ocean Southern Oscillation (SOI) events and those associated with solar sunspot and global geomagnetic activity will be evaluated. The strong correlation between Florida precipitation and the El Nino-Southern Oscillation has already been reported (Hanson and Maul, 1991) while the solar sunspot and geomagnetic connection to climate may be more widely debated. Recent research (Labitzke and van Loon, l 989, 1992) provide us with new evidence that an important connection exist between solar cycles and the earth climate.

In this study emphasis is placed on predicting extreme high and low periods of inflow to Lake Okeechobee. Figure l depicts the location of Lake Okeechobee in south central Florida. Lake Okeechobee is the second largest freshwater lake lying wholly within the boundaries of the United States. This lake is frequently referred to as the "liquid heart" of south Florida as it is an important source of freshwater for many of the natural ecosystems of south Florida, the primary source of supplemental water supply for over five hundred thousand

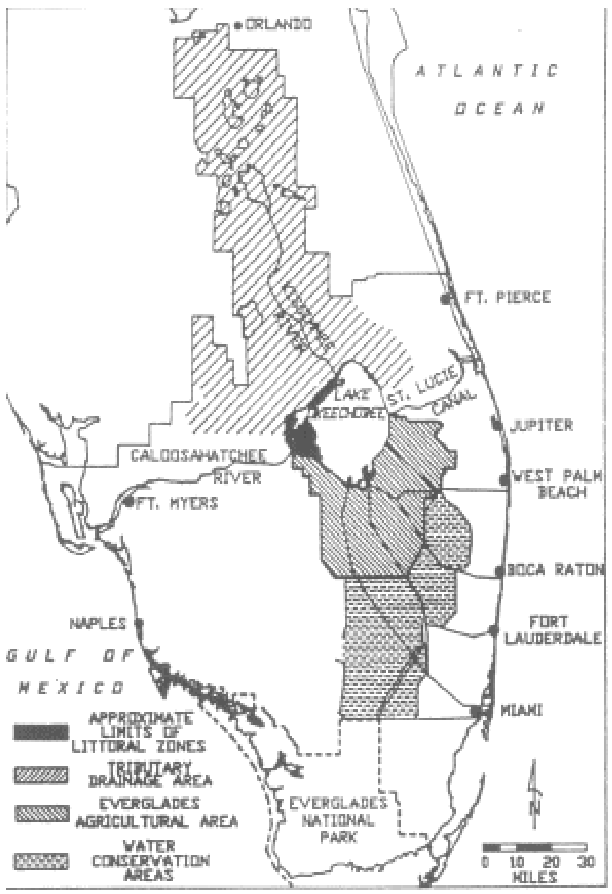

Figure 1. Location of Lake 0keechobee within South Florida Water Management District

acres of intensely farmed agricultural land, and is a backup source of water supply for the densely populated urban areas of south Florida. However, south Florida's potential for periods of heavy rains and severe tropical storms and Lake Okeechobee's large tributary basins require that water levels in the lake be carefully monitored to ensure that they do not rise to levels that would threaten the structural integrity of the levee system surrounding the lake. Therefore, when water levels in the lake reach certain elevations designated by the operational schedules, discharges are made through the major outlets to control excessive buildup of water in the Lake. The timing and magnitude of these releases is not only important for preserving the flood protection of the regions, but also for protecting the natural habitats of Lake Okeechobee's littoral zone and estuaries downstream of the two major outlets. Extended periods of high water levels in the lake are stressful to the lake's littoral zone habitat, while large discharges to the estuaries cause undesirable changes to the downstream ecosystems.

Currently the Lake Okeechobee water level and discharge operational schedule is designed to equitably meet the competing objectives of water management within the region of south Florida (Trimble and Marban, 1989). However, this operation schedule was developed based on the most recent history of water levels in the Lake and the season of the year as the reliability of long term weather forecast and the relationship between global climate and local Florida hydrology was seen as, at best, only fair. With a improved understanding of the global climate - south Florida hydrology link and the application of neural networks for climate forecasting a more dynamic operational schedule may be developed in the future that reorderoperational priorities of the water management during different climate regimes. For example, during the wet periods prior to 1960 more emphasis may be put on lowering the water level in the lake to protect the lake littoral zone while during the post 1960 period more emphasis may be put on water supply since below normal rainfall threaten the ability to meet the water supply demands on the lake while the littoral zone received sufficient periods of lower water levels from lack of rainfall.

EL NINO - SOUTHERN OSCILLATION EVENT

The signature of an El Nino event is the occurrence of very warm ocean waters at low latitudes located off the west coast of South America. This region of the ocean normally has cooler sea surface temperatures due to the upwelling of the ocean. The Southern Oscillation Index (SOI) is the measure of sea level atmospheric pressure difference between Darwin Australia (western Pacific) and Tahiti (eastern Pacific). There is a strong connection between the El Nino event and the Southern Oscillation Index. The El Nino-Southern Oscillation Event is often referred to by the acronym ENSO. An event of this type affects the climate of a large portion of the planet. The strongest and most reliable effects occur in the tropical Pacific Ocean. Other parts of the world, especially in the middlelatitudes are affected through teleconnections. are represented as statistical associations among climatic variables separated bylarge distances.

Many large rainfall and drought events that occur within the state of Florida are strongly correlated to ENSO events (Hanson and Maul, 1991). This type of relationship is important to investigate farther for both operational and planning concerns. It must also be determined if ENSO events and the global teleconnections are changing as the climate changes due to global heating or the secular fluctuations of the climate. Evidence that the El Nino existed over four centuries ago is presented by Hanson and Maul (1989) and by Quin, et al. (1987). Recently, Wang (1995) reported on interdecadal changes of the El Nino onset. It is vital that water managers understand what effects these changes may have on the climate of Florida. In this analysis, we assumed the SOI to be synonymous with ENSO since the period of reliable record available to us was longer than the El Nino sea surface temperature anomalies. A negative SOI index is most often associated will, a warm sea surface temperature anomaly El Nino event while a positive SOI is synonymous with a cold sea surface anomaly La Nina event.

CLIMATE FLUCTUATIONS RELATED TO SOLAR SUNSPOT CYCLES

Global climate fluctuations that occur with a regular frequency may have their origins associated with solar activity. Sunspot activity displays a cyclic pattern with an approximate periodicity of Il years. The period may actually vary between, 9 and 14 years. Periods tend to be shorter when the peak of the sunspot activity is more pronounced and longer the peak is less pronounced. Between each II-year cycle there is a reversal in the direction of the sun's magnetic field. Therefore conditions only repeat themselves every 22-years. This 22-year period is known as the Hale cycle. Willet (1975, 1987) was able to relate global climatic shifts in detail to the Hale cycle. Longer secular sunspot cycles of about 90 and 180 years were also used by Willet to explain inter-decadal changes in the global climate.

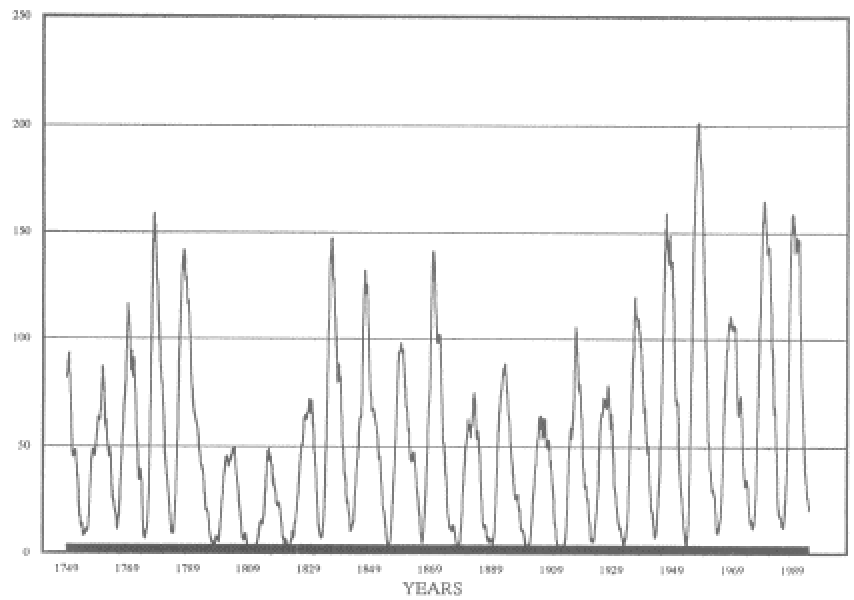

Figure 2. Relative sunspot number

Figure2 illustrates estimations of the relative sunspot numbers starting in the year 1750. These sunspot numbers were estimated by direct observation. Periods identified with the minimums of secular sunspot activity appear to be associated with periods of cool climates of the past. The period between 1800 and 1820 was the coldest globally since 1700. The period between 1425-1725 is believed to be the three centuries will, the lowest sunspot activity of the last thousand years. This period corresponds to the period known as the Little Ice Age. In spite of sonic statistical evidence of a relationship between solar sunspot cycles and the earth's climate fluctuations in certain parts of the world, no completely acceptable theory has been introduced that explains how the very small changes in the energy flux that enter the earth's atmosphere due to solar cycles can be translated into climatic fluctuations. Solar Sunspots are generally darker, cooler spots on the sun. However, other disturbances associated with the sunspots, such as solar flares and electromagnetic disturbances are also believed to contribute significantly' to climate fluctuations. According to Willet (1953) vigorous burst of ultraviolet radiation have their greatest effects at low latitudes, leaving the polar regions fairly cold and producing a zonal pattern of general circulation. Electromagnetic disturbances on the other hand, are protons and electrons that are diverted by the earth's magnetic field toward the magnetic poles and thus heat the upper air of [lie polar regions more than the tropics. The zonal circulations is disrupted will, a greater latitudinal transfer of air with accompanying storms and temperature extremes. This type of activity may best be estimated by geomagnetic activity as indicated by the aa index (Willet, 1987).

The possibility of explaining a significant portion of the climate fluctuations as caused by solar activity makes it more difficult to detect anthropogenic climate trends. For example, a strong global warming trend that occurred during [lie period from 1920 through 1950 was suggested by some to be entirely caused by [lie greenhouse effect. However, this same period was also a period of larger sunspot and solar flare activity which may also be related to [lie global heating during this period.

HISTORY OF ENSO, SOLAR ACTIVITY, GEOMAGNETIC ACTIVITY AND LAKE OKEECHOBEE TRIBUTARY INFLOW

Figure 3 illustrates the normalized sunspot and geomagnetic activity as estimated from a six month running average of the solar sunspot number and the aa index. The period from 1930 through 1960 contains three sunspot cycles that exhibit increasing sunspot and geomagnetic activity will, each cycle. The last cycle exhibits much larger activity than normal. Willet (1987) identified the period of the first three sunspot

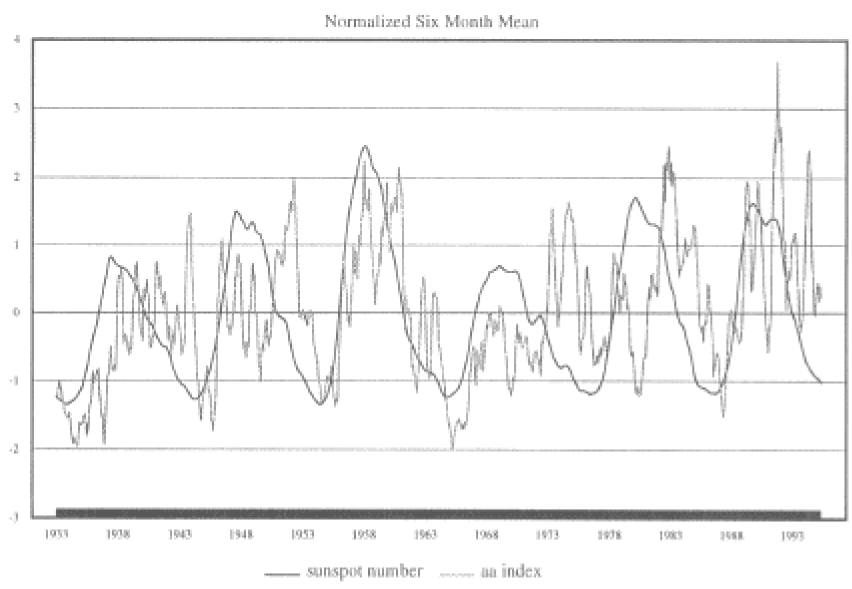

Figure 3. Sunspot number and aa index (Normalized six month mean)

cycles as being a period of the greatest global warming within the past 500 years. The third sunspot cycle occurred during a period in which Lake Okeechobee received it's four largest inflow years (1957-1960). High levels of geomagnetic disturbances continued throughout this period.

The fourth sunspot cycle which lasted from 1964 until 1978 is one of minimum solar activity. Below normal rainfall and droughts were characteristic of this period. Interestingly the

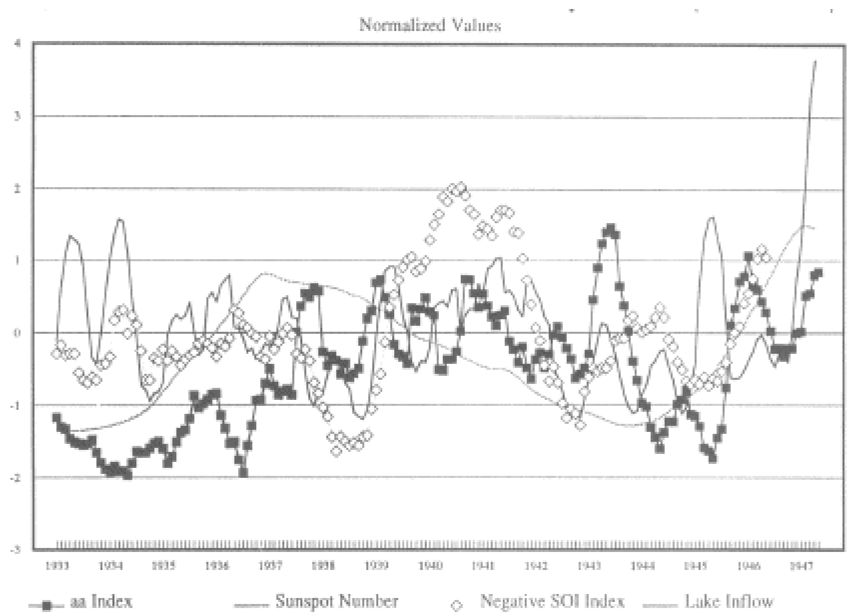

Figure 4. lake Okeechobee inflow versus key indices normalized values (1933-1947)

geomagnetic activity was delayed during this cycle so that the sunspot and geomagnetic activity were out of phase during the late 1970's and early 1980's. The minimum in geomagnetic activity associated with the minimum of sunspot activity of 1977 did not occur until the summer of 1981. This period was at the peak of 1980-1982 drought in south Florida and a time when Lake Okeechobee reached it's lowest recorded water level. Other drought periods including periods in the mid 1940's and the mid 1950's were also periods of low geomagnetic activity. This indicates that the geomagnetic activity may be an important predictor of south Florida climate. However, a period in the mid 1960's that experienced a lull in geomagnetic disturbances did not experience asimilar minimum in Lake inflows. This is likely do to the ENSO event that was occurring at about the same time.

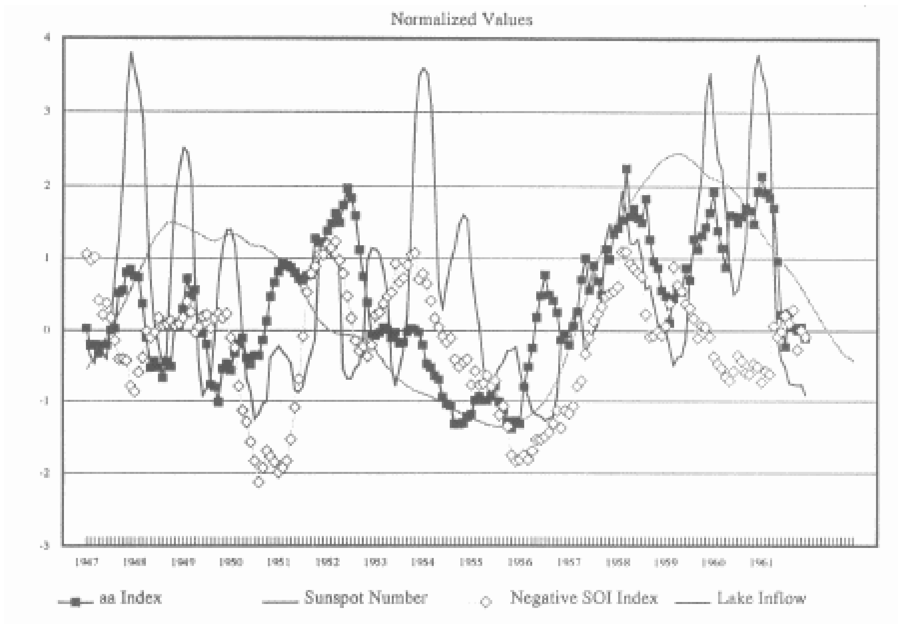

Figure 5. lake 0keechobee inflow versus key indices normalized values (1947-1961)

Hanson and Maul (1991) used Superposed Epoch Analysis to examined rainfall the years priorand during moderate to strong El Nino years. These El Nino years were defined as those events in which the El Nino Event lasted 2 years or more and that the year prior to the two years must be an non-El Nino year. The years they determined were strong El Nino years within our study period included: 1939-1940, 1957-1958, 1972-1973 and 1982-1983. Their most significant findings for Florida included: I) below normal rainfall over the entire state of Florida during the winter and spring the year prior to

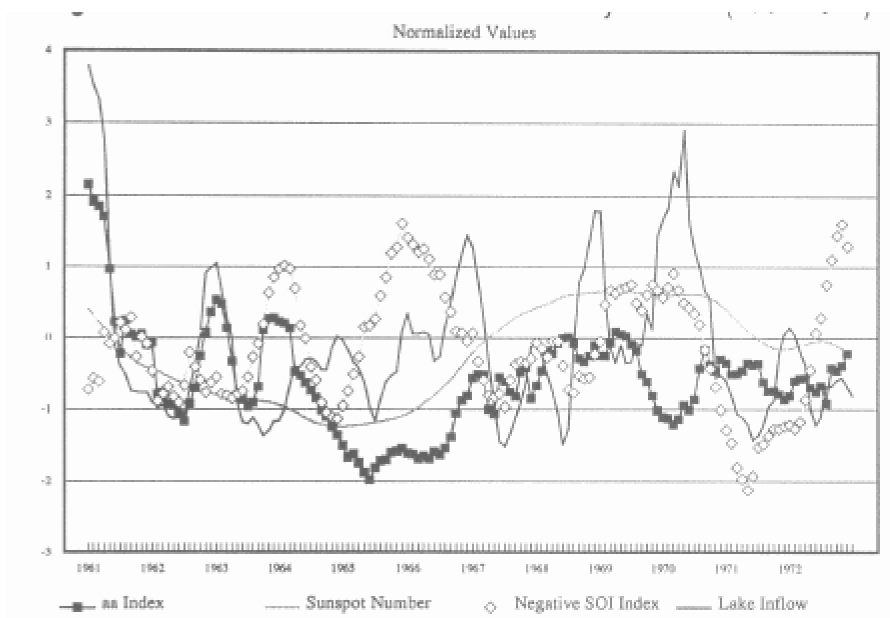

Figure 6 Lake 0keechobee inflow versus key indices normalized values (1961-1972)

an El Nino event; and, 2) above normal rainfall over all the state during the winter and spring of the second year of the anomaly. The rainfall anomalies were greatest over the southern half of the state ranging between 145% to 166% of normal.

Figures 4-8 illustrate the fluctuations of the SOI, the sunspot number, and the aa index in relationship to the normalized Lake Okeechobee inflow. All lines were smoothed by a 6 month moving average and normalized by subtracting the mean value and dividing by the standard deviation. Data source for the monthly

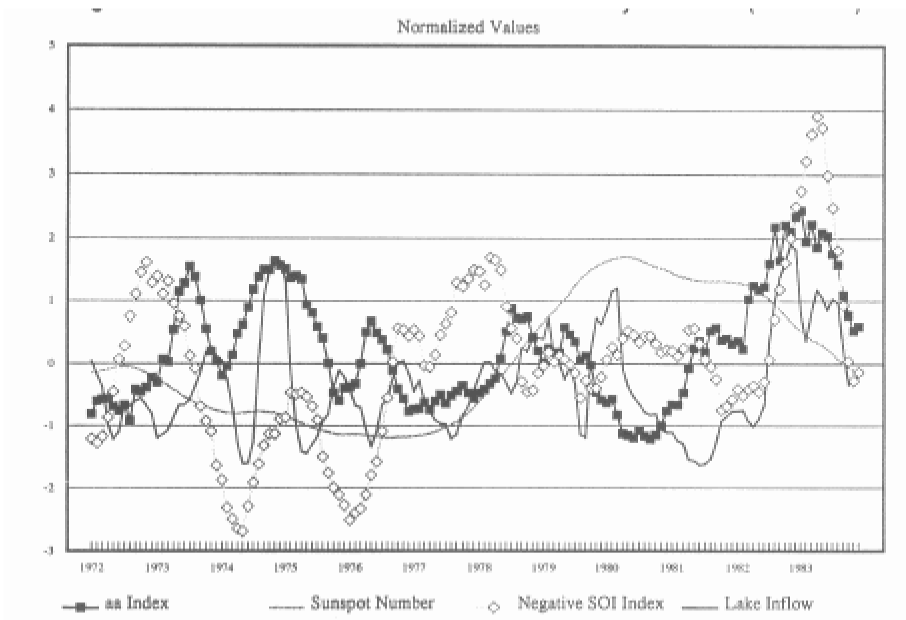

Figure 7 rake Okeechobee inflow versus key indices normalized values (1972-1983)

SOI was the Climate Analysis Center[1] while the monthly aa indices and sunspot number were obtained from the National Geophysical Data Center[2]. The Lake Okeechobee inflows include net rainfall on the Lake and are computed by adding historical outflows to the storage change estimated from water level fluctuations for a particular time period. Prior to 1963 the computed inflow values were obtained from the United States Army Corps of Engineers (1978). After 1963 values were computed from hydrologic data obtained from the South Florida Water Management District.

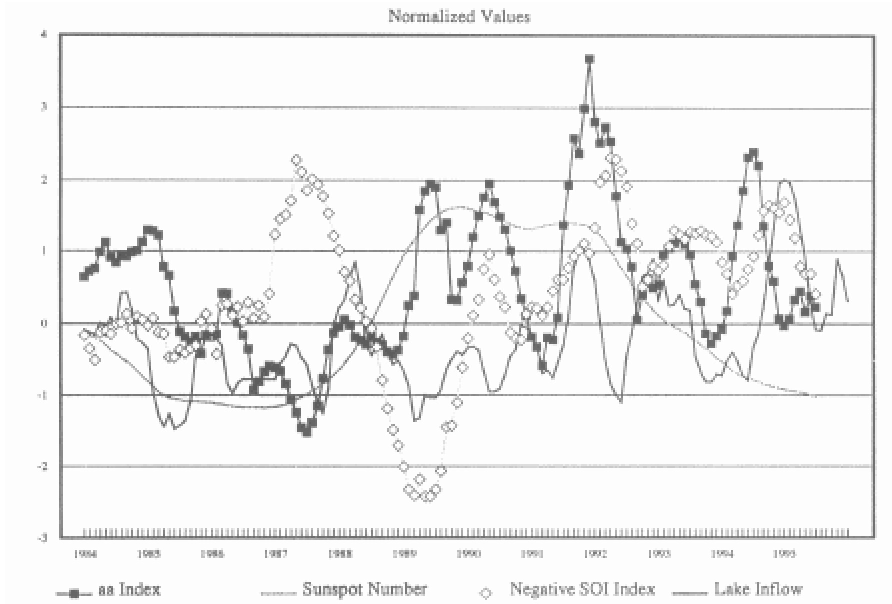

Figure 8. lake Okeechobee inflow versus key indices normalized values (1984-1995)

Large negative SOI values are indicative of an El Nino Event while large positive SOI values are indicative of an La Nina Event. An increase in Lake Okeechobee inflow with the El Nino-Southern Oscillation warm sea surface temperature is apparent. In fact all of the moderate and strong El Nino events reported on by Hanson and Maul and included in our period of study exhibited greater than normal Lake inflow except for the 1972-1973 El Nino events. In addition, the severe droughts of the mid 1940's, 1950's and early 1970's were marked by strong La Nina events. The effect of the 1972-1973 ENSO event was likely encouraged by the low geomagnetic activity during the same period.

It is interesting to note that the 1959-1960 period was not accompanied by an ENSO event (see Figure 5). The geomagnetic activity, however, remained very active during this period as Lake Okeechobee received it's largest two year inflow. Two separate peaks of large inflow to the Lake appear to correspond to separate peaks in electromagnetic activity. In addition, the drought of 1980-1982 appears to be associated with a minimum in geomagnetic activity and the sunspot and geomagnetic activity being out of phase with each other (see Figure 7). Paine (1983) presented a hypothesis that would connect large anomalies in rainfall along the eastern coast of North America during this period to solar activity. A weak La Nina event occurred in 1982 that may have had the effect of prolonging this drought after the geomagnetic activity increased in early 1982. To understand the factors effecting south and central Florida climate and therefore Lake Okeechobee inflow, the geomagnetic disturbances, sunspot number and ENSO events appear to need consideration in unison. During certain periods the effects of these processes may work together to enhance the likelihood of severe floods or droughts or sometimes to work against each other to lessen the likelihood of an extreme event. In addition to the indices discussed above the suns polarity and month of the year is included as input for the neural network.

A BRIEF INTRODUCTION OF ARTIFICIAL NEURAL NETWORKS

An artificial neural network (hereafter referred as neural network or network) is a computing method inspired by structure of brains and nerve systems. A typical neural network consists of a group of inter-connected processing units which are also called neurons. Each neuron makes its independent computation based upon a weighted sum of its inputs, and passes the results to other neurons in an organized fashion. Neurons receiving input data form the input layer, while those generate output to users form the output layer. A neural network must be trained by data for a problem. The training process is to adjust the connecting weights between each neurons so that the network can generalize the features of a problem and therefore to obtain desired results.

Among other advantages when compared with analytical approaches, the neural network approach does not require human expert knowledge in terms of mathematical descriptions of the problem. A neural network is trained from training data sets. This made neural network a desirable tool in dealing with complex systems, especially those of which the analytical descriptions may yet limited while their solutions are more of concerns, such as the problem discussed in this paper. The mathematically descriptive knowledge of the relationship between the solar activities and our regional climate fluctuations are limited, while the outcome of the climate may yield significant impact on water management.

Neural networks have received attention from many professions. In water resources and hydrology', neural network has also been finding its various applications (Karunanithi, et al., 1994; Smith and Eli, 1995; Crespo and Mora, 1993; Grubert, 1995; Raman and Sunilkumar, 1995; Derr and Slutz, 1994)

BACK PROPAGATION

Among the variety of neural network paradigms, the Back-propagation is the most common in use and has been applied successfully to a broad range of areas such as speech recognition, autonomous vehicle control, Pattern recognition, and image classification. Its training procedure is intuitive because of its relatively simple concept: adjust the weights to reduce the error.

Back-propagation networks topology are usually layered, with each layer fully connected to the layer before it and the one next to it. The input to the network propagates forward from the input layer, through each intermediate layer, to the output layer, resulting in the output response. when the network corrects its connecting weights, the correction process starts with the output inputs and propagates backward through each intermediate layer to the input layer - hence the term Back propagation.

A typical back-propagation neural network has three or more layers of processing units, Figure 9 shows the topology for a typical three-layer network. The left most layer of the network is the input layer, the only units in the network that receive input data. The middle layer is also called hidden layer, in which the processing units are interconnected to layers right and left. The right most layer is the output layer. Each processing unit is connected to every unit in the right layer and in the left layer, but it is not connected to other units in the same layer. A back-propagation network can have one or more than one hidden layers, although many have one or two hidden layers.

There are two phases in its training cycle, one to propagate the input pattern and the other to adapt the output. It is the errors that are backward propagated in the network iteration to the hidden layer(s).

A detail description of the mechanism of back-propagation neural network can be found in books in the field, such as the one by Rumelhart and MaClelland, 1986.

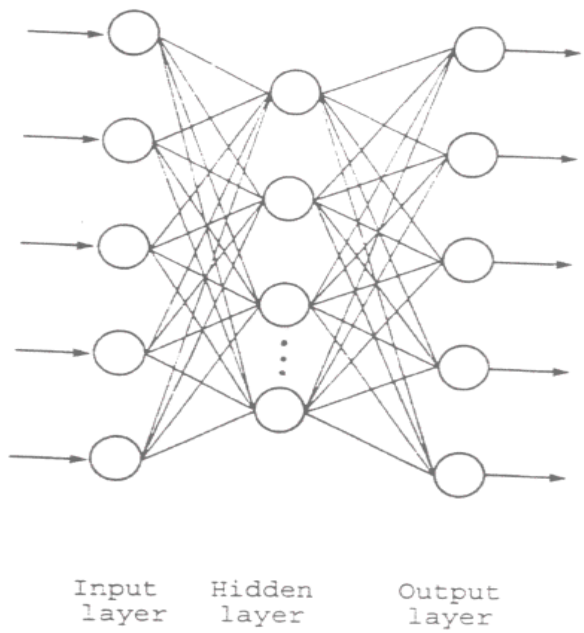

Figure 9. Schematics of a three-layer, back-propagation neural network

CHOOSING A NETWORK CONFIGURATION

The size of input layer and output layer are fixed by the number of inputs arid outputs our prediction requires, i.e., 5 input layer neurons for all the five input variables, a single output neuron for the predicted change of inflow to the Lake Okeechobee. there is no universally applicable formula to be used for deciding the size of middle layers. In general, networks with too many hidden neurons tend to memorize the input patterns and may lack of generalization, while those with too few hidden neurons may not be able to simulate a complex system at all. In the former case, a network responses to the training data very well, but when presented with the data it has not seen before, it fails to generate responsive outputs. In the latter case, a network may not have sufficient dimensions to be trained for the problem and its performance may not be improved no matter how much training it received. A network with more hidden neurons also requires more computing power and more training time needed. The best way to determined the number of middle layers and their sizes is trial-and-error. This can also be helpful to reveal the underlining relationships between variables. The rule of thumb is to start with the smallest size possible for a given problem to allow for generalization, then to increase the size of the middle layer(s), until the optimal results achieved.

We experimented with both one and two hidden layer configurations, with the size ranging from 3 neurons to 11 neurons, and found the one hidden layer with 6 neurons most suitable to the problem.

INPUT DATA PREPARATION

This procedure is crucial to the success of applying neural network approach. The performance of a neural network largely depend upon the data set it was trained. in general, the better the training data sets represent the objective system, the better performance of the neural network. The preparation includes the selection of input variables, the examination of the data to eliminate bad data points, averaging, and normalizing.

The selection of input variables is solely problem dependent. After analyze the problem, five variables were chosen for this study. They are: Southern Oscillation Index (SOI), Sun Spot Number (SSN), aa-index, polarity index, and month index.

Extraneous data are not relevant to the generalization and therefore need to be carefully' eliminated. All our input data were examined for eliminating spikes resulting from bad data.

Our goal is to use the information of past 6 months, including current month, to predict future 6 months inflow to the Lake Okeechobee. Therefore, a six month running averaging is applied to the raw data. All input variables were averaged for past six months, including current month, and the observed inflow data was averaged for the future 6 months. This is also necessary to further factor out local noises of the data (Derr and Slutz, 1994).

Because neurons at the middle layer fire when their input data exceeds a threshold, neural network are more responsive to a particular range of input data, it is necessary to normalize the data to the range from 0 to 1. This was done in two steps. Step one, normalizes each variable by using its respective mean and standard deviation as follows: normalized value = (original value - mean)'standard deviation; and, Step two, uses Sigmoid function to further normalize the data to the range from 0 to 1.

NETWORK TRAINING

The prepared data are 6 time series data sets, 5 for input variables and one for the target values. The duration of this time series ranging from March, 1933 to July, 1995. Each set was divided into two sections, one for training and the other for testing. An assumption on which this prediction is based is that the past data provide adequate patterns from which future events may be deduced. The duration for training data is from

March 1933 through April 1987, total 650 averaged monthly data points. The duration for the testing data is from May 1987 through July 1995, total 99 data points.

All the training and testing of the neural network was done on a SPARC 20 workstation,. Typical training times located between one to five hours.

RESULTS AND CONCLUSION

After training, the testing data were presented to the network to generate the prediction results. It was found that a network configuration of one hidden layer of the size of 6 neurons achieved the best prediction results as shown in Figure 10. The best data set contained a moderately severe dry period from September 1988 through May 1990 and the very wet year of 1994. The neural network was able to predict both of these events illustrating the sensitivity of south central Florida's hydrologic conditions to the global climate factors. The best global indicator of a possible drought during the 1988-1989 period was a very strong La Nina that

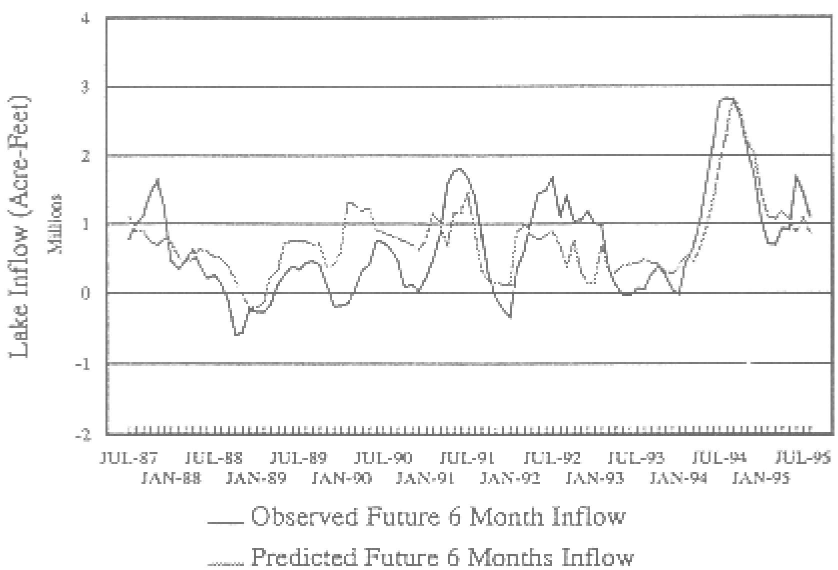

Figure 10. lake Okeechobee predicted versus actual inflow (6middle layer neurons - predictors: Sol, sunspot number, aa index, polarity and month)

occurred during this period. The geomagnetic activity was high during this period and appears to be out of phase with thee SOI as an indicator of drought for the region (see Figure 8). This likely explains why the network did not predict as severe a drought as the one that actually occurred and might be expected by the strong La Nina event. The magnitude of
the peak of the 1994 period was better predicted by the network. The predictions may possibly be refined by also training the neural network with trends of global indices. The predictor should be useful for operation purposes of Lake Okeechobee when used in conjunction with existing hydrologic conditions in the Lake Okeechobee tributary basins and the Lake Okeechobee water level.

The increase in geomagnetic activity in 1989 may have been a precursor of things to come. This high level of activity has continued through the 1990's. Inflows to Lake Okeechobee have returned to more normal levels as illustrated in Figure 11. There has also been an extended El Nino event that enhanced flows during this period. The last three decades have been very dry for south central Florida as indicted in this same figure. The neural network was able indicate the return to a wetter conditions.

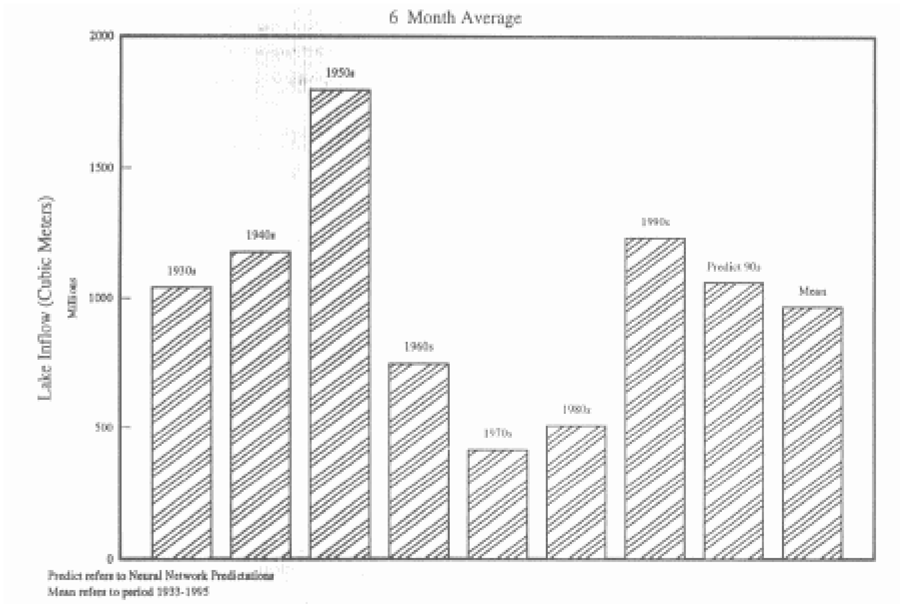

Figure 11. Decadal shifts of average inflow (predict refers toneural network predictions - mean refers to period 1933-1995)

FUTURE STUDIES

The results of this research, in addition to providing a tool for refining water management practices, leads to interesting questions. The interdecadal fluctuations of inflows to Lake Okeechobee appear to be tied to fluctuations in solar activity. How are the climate shifts due to natural fluctuations and those of a permanent shift such that might be caused by increasing the greenhouse effect isolated'? Can long term solar cycles and greenhouse warming be predicted well enough so that interdecadal changes in climate can be predicted!? Could this information be used to refined water management short term practices or long term plans!7 Can neural network technology aid in determining climate shifts?

It will be interesting to explore the neural network to predict five or ten years of Lake inflows to see if longer term climate shifts can be predicted by a neural network. Iii addition, experiments including other global inputs such as the Pacific-North American (PNA) index, the Quasi-Biennial Oscillation, and the North Atlantic Oscillation need to be considered. Rainfall and temperature anomalies in Florida also seem related to global

Rainfall and temperature anomalies in Florida also seem related to global rainfall and temperature anomalies and may also be considered as input to the neural network.

Comparison to the predictions of traditional methods such as statistical analysis is also desirable.

ACKNOWLEDGEMENTS

Bob Hamrick's expressed concerns related to the effects of climate shifts on water resource management and his interest in the state-of-the-art computer technology helped inspire this research

FOOTNOTES

1:Climate Analysis Center, Camp Springs, Maryland, U.S.A

2:National Geophysical Data Center, Boulder, Colorado, U.S.A.

REFERENCE

Chin, P.A., Analysis and Prediction of South Florida Rainfall Technical Report No. CEN-93-2, University Of Miami, Miami, FL (1993).

Crespo, J.L. and E. Mora, Drought estimation with neural networks, Advances in Engineering Software, 18 (1993).

Derr, Vernon E. and Ralf J. Slutz, Prediction of El Nino Events in the Pacific by Means of Neural Networks, AI Applications 8,51(1994).

Grubert, John P., Predietion of Estuarine Instabilities with Artificial Neural Networks, Journal of Computing in Civil Engineering, 226(1995).

Hanson, K. and G.A. Maul. Florida Precipitation and The Pacific El Nino, 1859-1989, Florida Scientist, 54, pp. 160-168(1991). Labitzke, K. and H. van Loon, Association Between the 11-Year Cycle, the QBO and the Atmosphere, Journal of Climate, 2(1989). Lahitzke, K. and H. van Loon, Association between the 11-Year Cycle and the Solar Cycle, Journal of Climate Part 5, 5(1992).

Nachimuthu, Karunanithi, et al., Neural Networks for River Flow Prediction, Journal of Computing in Civil Engineering, 8,201(1994).

Paine, D.A., Climate hypothesis Describing the Terrestrial System as a Frequency Domain with Specific Response Characteristics, American Geophysieal Union, 64, No. 26, (1983).

Quin, ,W.H.,V.T. Neal, and S.E. Antunez De Moyola, El Nino Occurrences over the past four and a half centuries, Journal Geophysical Research, 92(1987).

Raman, H. and N. Sunilkumar, Multi-varriate modeling of water resources time series using artificial neural networks, Hydrological Sciences, 40(1995).

Ramusson, E.U. and P.A. Arkin, A Global View of Large Scale Precipitation Variability, Journal of Climate, 6 (1993).

Rumelhart, P.E. and J.L. MeClelland, Parallel Distributed Proceesing MIT Press, Cambridge, Mass (1986).

Smith, Jason and Robert N. Eli, Neural Networks Models of Rainfall-Runoff Process, Journal of Water Resources Planning and Management; 121,56(1995).

Trimb]e P.J. and J.A. Marban, A Proposed Modification To Regulation Of Lake Okeechobee, Water Resources Bulletin, 25(1989).

United States Army Corps of Engineers, Central and Southern Florida Project, Rules and key Operating Criteria. Master Manual, Jacksonville District, Jacksonville, Florida (1978).

Wang, B., Interdecadal Changes In El Nino in the Last Four Decades, Journal of Climate, 8(1995).

Willet, H.C., Atmospheric and Ocean Circulations as Factors in Glacial-Interglacial Changes of Climate, Climate Change, Harvard University Press, Cambridge Mass., pp. 51-71(1953).

Willet, H.C., The Sun as a Maker of Weather and Climate Technology Review: pp. 47-55(1976).

Willet, H.C., Climatee Responses to Variable Solar Activity-Past Present and Predicted MIT, Cambridge, in Michael R.N. Rampino, Climate History, Periodicity, Predictability, Van Nostrand Reinhold Company, Inc. (1987).